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Ontology-based Semantic Approach for Learning Object Recommendation

Noppamas Pukkhem
Department of Computer and Information Technology
Faculty of Science, Thaksin University, Phattalung, Thailand 93110
Email: noppamas@tsu.ac.th

***Abstract*— The main focus of this paper is to apply an ontology-based approach for semantic learning object recommendation towards personalized e-learning systems. Ontologies for learner model, learning objects and semantic mapping rules are proposed. The recommender can be able to provide individually learning object by taking the learner preferences and styles, which used to adjust or fine-tune in learning object recommending process. In the proposed framework, we demonstrated how the ontologies can be used to enable machines to interpret and process learning resources in recommendation system. The recommendation consists of four steps: semantic mapping between learner and learning objects, preference score calculation, learning object ranking and recommending the learning object. As a result, a personalized and most suitable learning object is recommended to the learner.**

***Index Terms*— learning object, ontology, recommender, semantic web.**

I. Introduction

Online digital learning resources are commonly referred to as learning objects in e-learning systems. They will be a fundamental change way of thinking about digital learning content. Actually, learning objects can be learning components presented in any format and stored in learning object repositories which facilitate various functions, such as learning object generation, search, review, etc. Rapidly evolving internet and web technologies have enabled using learning objects in Learning Management System, but the problem is that it does not offer personalized services and dues to the non-personalized problem. All learners being given access to the same set of learning objects without taking into consider the difference in goals, prior knowledge, motivation and interest. This gives result in lack of learner information to perform accurate recommending of the most suitable learning objects. This work provides prior knowledge about learners and learning objects in semantic web approach that can be used in our semantic-based recommendation model.

Ontology is an important tool in representing knowledge of any resources in WWW. Until now, knowledge bases are still built with little sharing or reusing in related domains. In the future, intelligent systems developments will have a repository of ontologies rather than generating the new one, they will assemble knowledge bases from the repository. This should greatly reduce implement time while improving the system robustness and reliability. Our focus is on developing the ontology-based model inorder to present the knowledge about the learner, learning object and propose an effective process for enhancing learning object selection of learners through our recommendation model.

The remainder of this paper is organized as follows. Section II gives background and previous work. An overview of learning object concept, learning style and related works is also included. Section III presents the analysis and design of learning objects and learner model ontology. Then, section IV, we propose our designing of learning object recommendation model. Next, we describe the detail of all proposed learning object recommendation algorithms. Finally, section V concludes this paper, giving a summary of its main contribution and pointing towards future research directions.

II. Background knowledge and previous work

A. Learning Object

Learning objects are a new way of thinking about learning content design, development and reuse. Instead of providing all of the material for an entire course or lecture, a learning object only seeks to provide material for a single lesson or lesson-topic within a larger course. Examples of learning objects include simulations, interactive data sets, exercises, assessments, annotated texts, and adaptive learning component. In general, learning objects have the following characteristics; self-contained, can be aggregated, reusable, can be aggregated, tagged with metadata, just enough, just in time and just for you [1].

A learning object does not have a predefined size. Granularity of a learning object can extend from sub-topics to topics to lessons, and their associated media elements. Collections of learning object topics aggregate to form raw asset, topics, lessons, parts, courses, and curriculum libraries.

B. Learning Object Metadata

International efforts have been made on developing standards and specifications about learning objects since late 1990's. IEEE Learning Technology Standards Committee, IMS Global Learning Consortium, Inc., and CanCore Initiative [2] are organizations active in this area.

IEEE LOM Standard is a multipart standard, which is composed of Standard for Learning Object Metadata Data Model, Standard for XML Binding and Standard for RDF Binding. The first part of the standard, IEEE 1484.12.1 LOM

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Data Model standard [3], has been accredited and released. The LOM Data Model is the core of existing metadata specifications. It defines a hierarchical structure for describing a learning object. Table 1 shows a LOM instance, relevant characteristics of learning object are represented by data elements that are grouped into nine categories; *General, Lifecycle, Technical, Meta-metadata, Educational, Relation, Rights, Classification and Annotation*.

TABLE I: THE DESCRIPTION OF LOM CATEGORIES [3]

Category	Description
General	The general information about the resource.
Lifecycle	The feature related to the history and current state of the resource.
Meta-metadata	Information about the meta-data record itself.
Technical	The technical requirement and characteristics of the resource.
Educational	The educational and pedagogic characteristics of the resource.
Rights	The intellectual property rights and conditions of use for the resource.
Relation	The feature that defines the relationship between this resource and other targeted resources.
Annotation	The comment on the educational use of the resource and information on when and by whom the comment were created
Classification	The description that describes where this resource falls within a particular classification system.

C. Learning Style

Learning style is an important criterion towards providing personalization, since they have a significant influence on the learning process. Attempting to represent the learners' learning styles and adapting the learning object so as the most suit them is a challenging research goal. Learning style designates everything that is characteristic for an individual when the learner is learning, i.e. a specific manner of approaching a learning activity, the learning strategies activated in order to fulfill the task.

Felder-Silverman learning style model [4] is the one of the most widely used learning style in adaptive hypermedia system. The suitable learning style models for finding the learning style of learners are concluded by Brown [5]:

- The model should be enabled for use with multimedia
- The model should be enabled for use with adaptive web-based education system
- The model should result a good degree of validity and reliability consistency and thus provide accurate evaluations of learning style
- The model should be easily administered to the learner

Another important reason noted by Sangineto [6], Felder-Silverman learning styles was widely experimented and validated on an engineering and science student population. Furthermore, this model contains useful pragmatic recommendations to customize teaching according to the students' profiles.

D. Semantic-Based Tools

There are several semantic-based tools for information extraction and transform into meaningful which can be used through the process of building ontology-based model in our work:

-*OWL (Web Ontology Language)* is a language for definition of web ontologies which explicitly represents the semantics of terms in vocabularies and its relationships between these terms [11]. This is an accepted standard, language and platform independent and well- formed XML-markup language.

-*XML Schema* is a structure of blocks of XML documents formatting, similar as DTD (Document Type Definition). It can be used to store content and document's structure, but not all knowledge about content can be represented in the tree structure, and it is time consuming to maintain the order of presentation of knowledge. So, only XML Schema is not reasonable to represent documents.

-*RDF (Resource Definition Framework)* is a set of recommendations for well-formed XML documents. It is a more data aspect framework than human aspect. So, it is designed for enabling machine processing rather than for ease of human understanding.

E. Previous Works

In our previous work [7], we developed the method for generating the course concept map called "Course Concept Map Combination Model: CMCM" (see the right box in Fig. 1). The course concept map is the domain model that represents all possible sequences of learning concept for a specific course [8]. The domain model stores the knowledge about the course preferences, instructor's characteristics and experiences. The main concept map was implemented by using the Cmaptool [9]. CmapTools is a suite of tools for generating and sharing concept maps in electronic form. CmapTools supports creating and modifying concept maps, as well as including navigational links from concepts to another concept maps and multi-media material such as diagrams, images and video, enabling the construction of rich knowledge models. The tools facilitate storage and access of concept maps on multiple servers, providing the network services required to support knowledge sharing across geographically-distant sites. Then, the concept map will be used as the block structure of contents for supporting learning object recommendation method (see the bottom box in Fig. 1) in this work.

Learner model development (Figure 1) initials with the process of the learners' learning style analysis using an index of learning styles (ILS) questionnaire. The ILS is a 44-question instrument designed to assess preference on the four dimensions of the Felder-Silverman learning style model. Each

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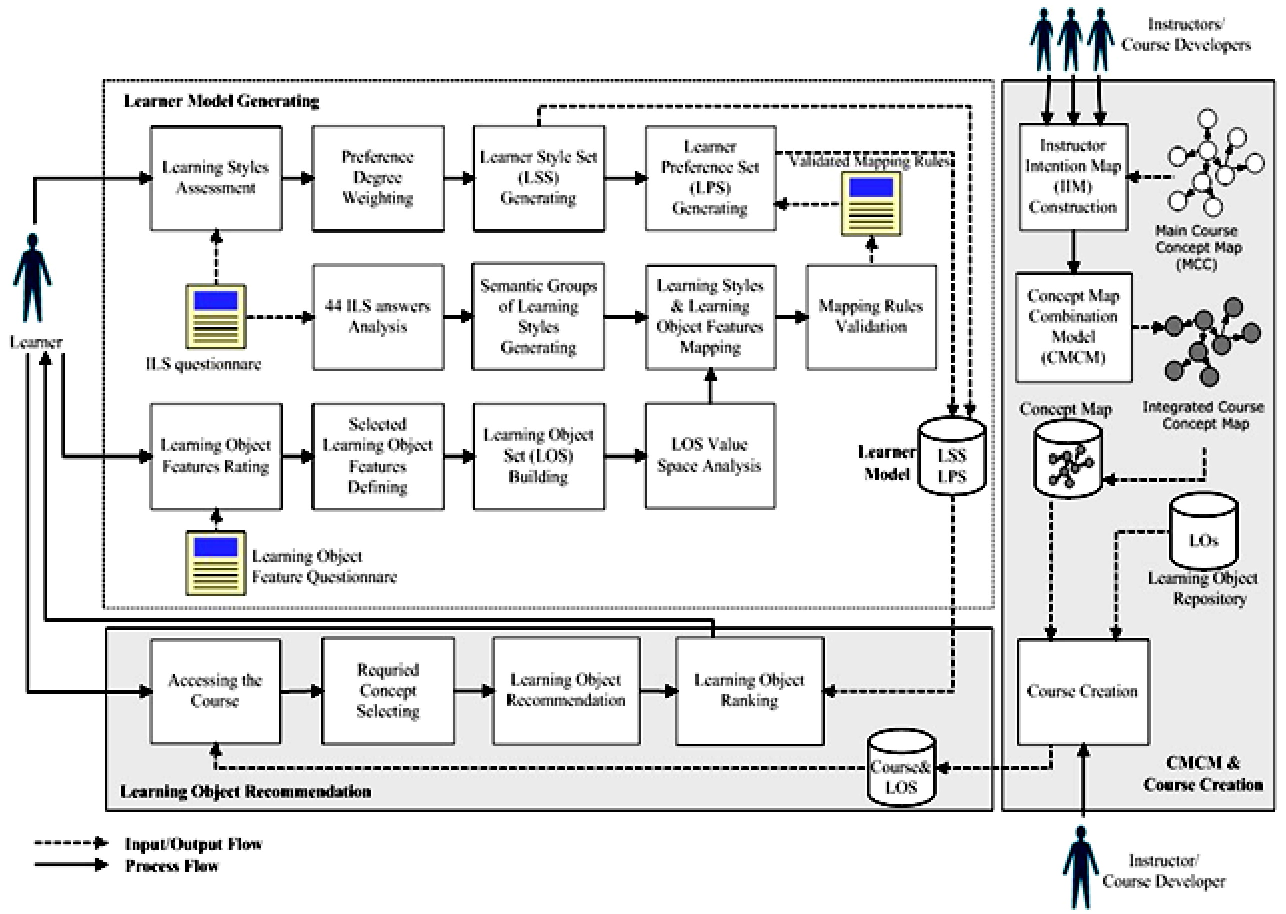

Fig.1. Our previous model for learning object recommendation based on learning styles [7]

TABLE II. INDICATIONS OF AN INDEX OF LEARNING STYLES

	Set of Questions	Symbol
Dimension 1	1, 5, 9, 13,17, 21, 25, 29,33, 37,41	**A**-**A**ctive **R**-**R**eflective
Dimension 2	2, 6, 10, 14, 18, 22, 30, 34, 38, 42	**S**-**S**ensing **I**-**I**ntuitive
Dimension 3	3, 7, 11, 15, 19, 23, 31, 35, 39, 43	**U**-Vis**U**al **B**-ver**B**al
Dimension 4	4, 8, 12, 16, 20, 24, 32, 36, 40, 44	**Q**-Se**Q**uential **G**-**G**lobal

dimension of the ILS has a 2-pan scale which represents one of the two categories (eg. Visual/Verbal). Table 2 shows the indications of the ILS.

The learner's responses are evaluated by the learning style indicator. Then learners are classified by a set of learning styles (SLS) that contains the learning style dimensions of each learner by assigning a weight parameter (0, 0.5 and 1).

Definition 1:

Set of Learning Styles : SLS(L) = {(S_i, Sw_i)} | S_i Î {A, R, S, I, U, B, Q, G } , Sw_i is the weight which has an interval [0-1] of each S_i and *i* is number of learning styles.

For example, for a particular learner L_1 we might have SLS(L_1)= {(A,0), (R,1), (S,0.5), (I,0.5), (U,0), (B, 1), (Q,0), (G,1)}

The SLS is a combination of each learning style and its weight. The learning object selection rules are used to identify the preferred learning object features for each learner and to create a learner preference set (LPS) that contains the preference of each learner. Both the SLS and LPS are stored in the learner model database .

In the next section, we will propose the ontologies-based model which adding the semantic approach for improving the knowledge representation of learner model and learning object model.

III. ONTOLOGY MODEL

To improve an affective model for the non-semantic model in our previous work, we extend ontologies to model knowledge about the learning objects, learners, and the mapping rules. With the domain knowledge representation, the term ontology refers to the explicit and formal description of domain concepts, which are conceived as a set of entities, instances, relations, axioms and functions [10]. By allowing learners or learning objects to share a common understanding of knowledge structure, the ontologies enable applications to interpret learner context and content features based on their ontologies in describing learning fields and build a practical model without starting from scratch. Personal model-based ontologies conceptualize and organizes knowledge of learned by a learner prior knowledges. The personalized learning objects are recommended using ontology structure.

In this work, we proposed three ontologies: Learner model ontology (describe about SLS), Learning Object Ontology

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(describe about LOS) and Mapping Rule Ontology. The detail of each ontology will describe in the next subsection.

A. Learner Model Ontology

In our recommendation system, information about a learner serves for recommending the learning object. It is used to define how to select the most suitable learning object based on a learner preferences and learning styles. Both of leaner style sets and learner preference set will be stored in the learner model database. The overall processes are presented in Fig. 2. and the detail of each process will be explained in subsection below.

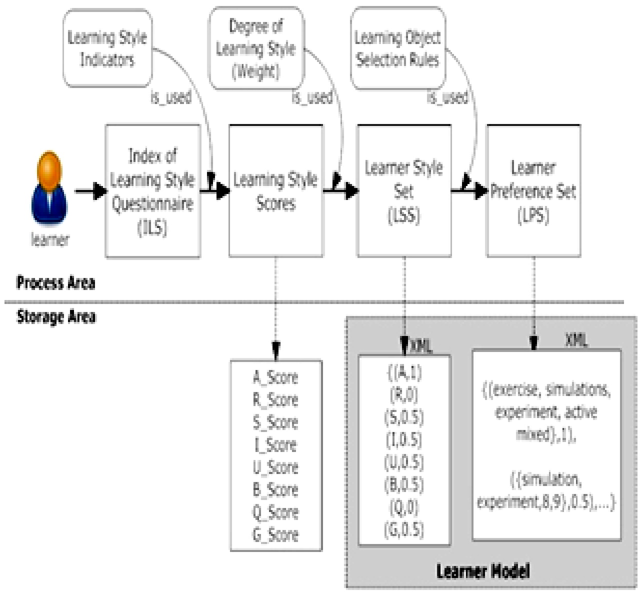

Fig. 2. Overall processes of learner model creation

The learner model is described by ontology-based for conceptualizing and exploited by the inference engine. The learner ontology show in Fig. 3 depicts contexts about a learner that corresponding with following defined definition 1. We are collecting learning style scores of a learner in four learning style dimensions (A/R, S/I, U/B and Q/G) which are their weight have an interval 0-1. The relation between a learner and their learning styles certifies by hasActiveScore, hasVerbalScore, hasReflectiveScore, hasSensingScore, hasSequentialScore, hasIntuitiveScore, hasVisualScore and hasGlobalScore. The hasPreferred relation is indicated to related learning object which the learner prefers to learn. ls and dc stand for Learning Style namespace and Dublin Core, respectively.

We adopt OWL (Web Ontology Language) to express ontology enabling expressive knowledge description and information interoperability of knowledge. According to the learner model ontology, the following OWL based markup segment describes the user contexts (learner) about "Learner1".

```
<?xml version="1.0" encoding="iso-8859-1"?>
<rdf:RDF xml: lang="en"
xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#"
xmlns:dc= "http://purl.org/dc/elements/1.1/"
```

Fig.3. Learner Model Ontology

```
xmlns:ls = "http://www.tsu.ac.th/csit/ls/ls-desc">

<rdf:Description rdf:about="Learner1">
<ls:hasActiveScore>0</ls:hasActiveScore>
<ls:hasReflectiveScore>1</ls:hasReflectiveScore>
<ls:hasSensingScore>0.5</ls:hasSensingScore>
<ls:hasIntuitiveScore>0.5</ls:hasIntuitiveScore>
<ls:hasVisualScore>0</ls:hasVisualScore>
<ls:hasVerbalScore>1</ls:hasVerbalScore>
<ls:hasSequentialScore>0</ls:hasSequentialScore>
<ls:hasGlobalScore>1</ls:hasGlobalScore>
<hasPreferred>
     <learningObject id="LO001">
          <dc:title>LO1</dc:title>
          <dc:format>video</dc:format>
          ...
          </learningObject>
</hasPreferred>
...
 </rdf:Description>
</rdf:RDF>
```

B. Learning Object Ontology

Properties of learning objects as well as relationships to other learning objects are defined by the learning object ontology. The LOM standard ontology is presented in Fig. 4.

The features and their value space based on IEEE LOM metadata [3] in the proposed recommendation algorithm are identified in Table 3. In our work, the learning object ontology describes about the properties of learning objects with five LOM features; format, interactivity type, interactivity level, semantic density and learning resource type. We define this feature set when used to describe learning object by definition 2 and the learning object class ontology is presented in Fig.5.

<u>Definition 2:</u>

Learning Object Set: LOS_{LO} is the discrete set of all selected learning object feature for describing the characteristic of the specific learning object.
is denoted by

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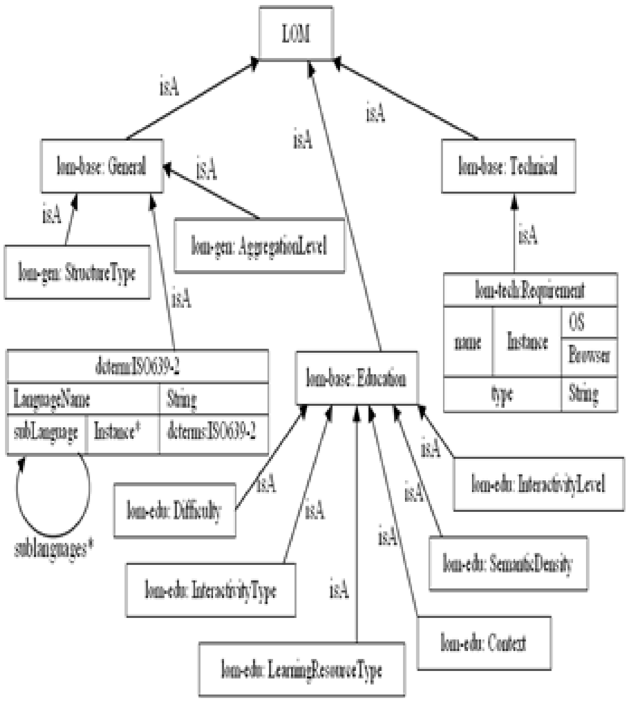

Fig. 4. IEEE LOM standard ontology

TABLE III. THE SELECTED FEATURES FOR LEARNING OBJECT RECOMMENDATION ALGORITHM

ID	Name	Element Path	Value Space
F1	Format	LOM/Technical/Format	Video, Image,Text, Audio, Animation
F2	Interactivity Type	LOM/Educational/ Interactivity_Type	Active, Expositive, Mixed
F3	Interactivity Level	LOM/Educational/ Interactivity_Level	Very low (0), Low (1), Medium (2), High (3), Very high (4)
F4	Semantic Density	LOM/Educational/ Semantic_Density	Very low (5), Low (6), Medium (7), High (8), Very high (9)
F5	Learning Resource Type	LOM/Educational/ Learning_Resource_Type	Exercise, Experiment, Definition, Algorithm, Example, Slide,Index

$$LOS_{LO} = \{F_1, F_2, F_3, F_4, F_5 \mid \forall F_i \in LOM, F_i \neq F_j\}$$

According to the representation of learning object ontology, the following OWL based markup segment describes the learning object (LOS) about “LearningObject1”.

```
<?xml version=”1.0" encoding=”iso-8859-1"?>
<rdf:RDF
xmlns:rdf=”http://www.w3.org/1999/02/22-rdf-syntax-ns#”
xmlns:dc= “http://purl.org/dc/elements/1.1/”
<rdf:Description rdf:about=”LearningObject1">
<LOS>
```

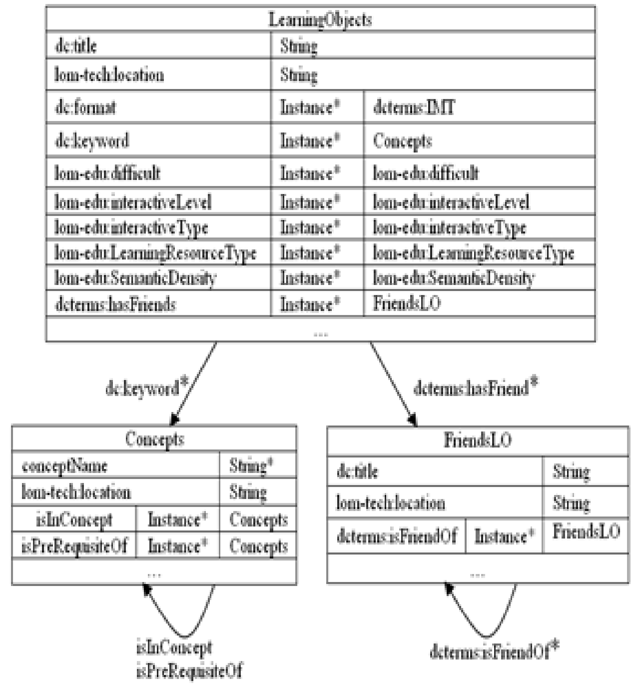

Fig. 5. Learning object class ontology

```
<itTitleIs> Operation System</itTitleIs >
<itInteractivityTypeIs>Active </itInteractivityType>
<itInteractivityLevelIs>Medium</itInteractivityLevelIs>
<itSemanticDensityIs>Medium</itSemanticDensityIs >
<itLeaningResourceTypeIs>Slide<itLeaningResourceTypeIs>
</LOS>
...
 </rdf:Description>
</rdf:RDF>
```

For creating the LPS that describes the preferred learning object features of learner, we develop the learning object mapping rules for matching the learner preference to suitable features of learning object (LO-learner preference matching).

The valid rule is the rule that is the member of the intersection set of word meaning between semantic group (SG) and LOS features. Table 4 shows the detail of semantic mapping, the semantic groups (SG) within the dimensions provide relevant information in order to identify learning styles. If a learner has a preference for tends to be more impersonal oriented and trying things out learner would have a balanced learning style on the active/reflective dimension. However, a learner has also a balanced learning style if they tend to be more socially oriented and prefer to think about the material. Although both learners have different preferences and therefore different behavior in an online course, both are considered according to the result of ILS. Considering the proposed semantic groups leads therefore to more accurate information about the learners’ preferences and to a more accurate model for identifying learning styles based on the behavior of learners in an online course.

C. Mapping Rules Construction and Validation

A common way to perform the analysis of mapping is to let the domain knowledge of learning style and learning ob

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TABLE IV . EXAMPLE OF SEMANTIC GROUPS ASSOCIATED WITH THE ILS

Learning Style	Semantic Group	ILS indicator # 'a'	ILS indicator # 'b'	Extracted words
A-Active	Social oriented (SG2)	5	-	Talk
		9		Contribute idea
		13		Group
		21		Group
		33		Group
		37		Group, outgoing
		41		Group
R-Reflective	Think about material (SG3)	-	1	Think it though
			5	Think about it
			17	Try to understand
			25	Think about it
			29	Think about it
	Independent (SG4)	-	9	Listen
			13	Independent
			21	Independent
			33	Independent
			37	Independent, reserved
			41	Independent

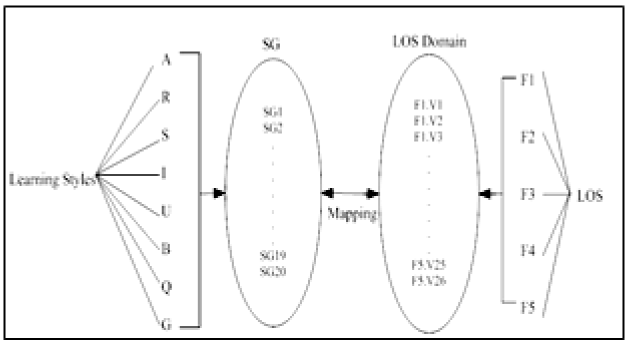

Fig.6. Semantic mapping between learning style and LOS features

ject features performs this task, and word analysis to support this process. In the proposed approach, learning style and learning object feature mapping rules discovered with Learning Object Set (LOS) domain are validated by the expert, and based on they represent the actual behaviors of the learner, some rules are "accepted" and some "rejected" by the expert.

All mapping rules are collected into one set. The mapping rule validation process is performed as a second part of Phase II. This process is described in Fig.6. All mapping rules are considered invalidated. We analyze the meaning of extracted words from 44 ILS answers and compare with learning object features in LOS. Then, the validation mapping as O is defined and applies them successively to the set of invalidating mapping rules. The application of each validation results in validation of some of the rules. In particular, some mapping rules get accepted and some rejected (sets O_{accept} and O_{reject} in Algorithm 1). Then, the next validation mapping would be applied to the set of the remaining invalidated rules (set $MR_{invalid}$). This validation process stops when the Terminate Validation Process condition is met. Our condition is that the set of validated mapping rules is covered by LOS domain. After the process is stopped, the set of all the discovered rules (MR_{all}) is split into three sets: accepted rules (MR_{accept}), rejected rules (MR_{reject}), and possibly some remaining invalidated rules ($MR_{invalid}$). At the end of Phase II all the accepted mapping rules are used to transform the learning style set (SLS) to learner preference set (LPS).

Process 1: Mapping Rules Validation Process

INPUT: Set of all discovered mapping rules MR_{all}.
OUTPUT: Sets of mapping rules MR_{accept}, MR_{reject}, $MR_{invalid}$ such that

$$MR_{all} = MR_{accept} \cup MR_{reject} \cup MR_{invalid}$$

METHODS:

$MR_{invalid} := MR_{all}$, $MR_{accept} := f$, $MR_{reject} := f$.
While (not TerminateValidationProcess()) begin
Expert selects a validation operator (called, O) from the set of available validation mapping.
O is applied to $MR_{invalid}$, Result: disjoint sets O_{accept} and O_{reject}.
$MR_{invalid} := MR_{invalid} - O_{accept} - O_{reject}$,
$MR_{accept} := MR_{accept} \cup O_{accept}$,
$MR_{reject} := MR_{reject} \cup O_{reject}$
End

Based on Felder and Silverman learning style model, the association between each learning style and the learning object features is analyzed. We demonstrate the example of validated mapping rule selection from all possible mapping rules as follows.

Mapping 1. Recommend learning object for "**A-A**ctive" learner

If "A" $\in$ SLS(L)

Then LOM.educational.interactivity_type = "active" or "mixed"
And LOM.educational.LearningResourceType = "exercise" or "simulations" or "experiment"

Mapping 2. Recommend learning object for "**R-R**eflective" learner

If "R" $\in$ SLS(L)

Then LOM.educational.interactivity_type = "expositive"
And LOM.educational.ResourceType = "definition" or "algorithm" or "example"

Fig. 7-8. demonstrates the example of validated mapping rule selection from all possible mapping rules.

Based on the process of word analysis process, the example of proposed mapping rules accepting (validation mappings O in process 1) is demonstrated as follows:

Mapping 3.

Sensing := {realistic, reality, sensible, fact, certainly, concrete, careful detail, existing way}
Map to:
Semantic Density
Semantic density := "very low":= {message, text}
Semantic density :="low":= {definition, image}
Semantic density := "medium":={audio}
Semantic density := "high":= {video, exercise}
Semantic density := "very high":= {simulation, experiment}

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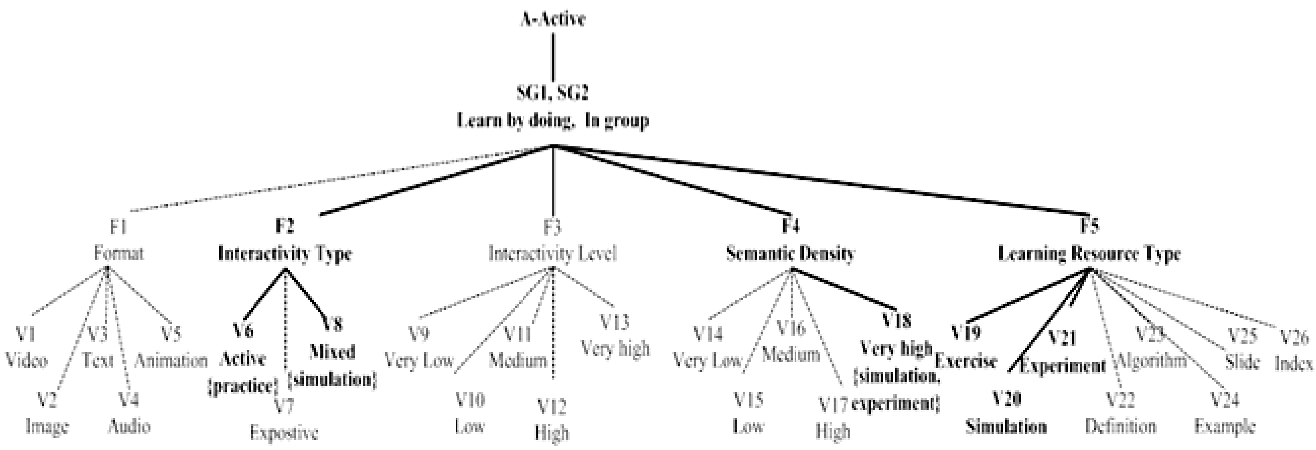

Fig. 7. Mapping active style to LOS features

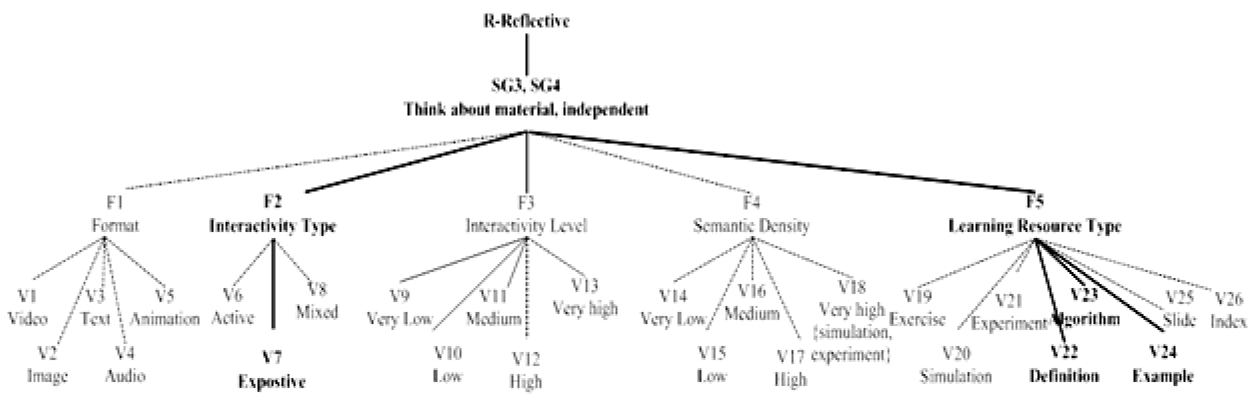

Fig. 8. Mapping reflective style to LOS features

Learning Resource Type

Learning resource type := "exercise":= { worksheet, tutorial, sequence of actions, assignment }

Learning resource type := "simulation":= { visual training ,behavior of some situation, }

Learning resource type := "experiment"= { establish some know truth, discover unknown, test hypothesis, }

Learning resource type="definition":= { objective , explanation, give meaning }

Learning resource type:="algorithm":={step for action}

Learning resource type:="example"= { show how to act, case study}

Learning resource type:="index":= { reference, glossary, list of content}

Next, the learner style set (SLS) will be considered with mapping rules for creating the learner preference set (LPS). The definition of LPS is shown in definition 3.

Definition 3: Learner Preference Set LPS is the set of learning object features which learner prefers to learn and its preferred height.

$LPS = \{(\{PF_i\}, Pw_i) | PF_i \in F_i, Fw_i \in \{0, 0.5, 1\}\}$

PF is preference feature and denoted by $PF = \{A, R, S, I, U, B, Q, G\}$,

Fw is feature weight and i is the number of the feature.

Both of SLS and LPS will be used as input values in the recommendation algorithm in the next section.

D. Extend Mapping Rule to Reasoning Rule

In this section we show rules are employed to reason over ontology-based model (learner model, learning object model). The communication between reasoning rules and the other resource information will take place by exchanging RDF annotations[12]. Several rules is can be derived.

1. Person := Learner
2. Resource := LearningObject
3. LearningStyle:= Active ∪ Reflective ∪ Sensing ∪ Intuitive ∪ Visual ∪ Verbal ∪ Sequential Global
4. ActiveLearner := Person) ∩ Active
5. ReflectiveLearner := Person) ∩ Reflective
6. SensingLearner := Person) ∩ Sensing
7. IntuitiveLearner := Person) ∩ Intuitive
8. VisualLearner := Person) ∩ Visual
9. VerbalLearner := Person) ∩ Verbal
10. SequentialLearner := Person) ∩ Sequential
11. GlobalLearner := Person) ∩ Global
12. LOFeature:= forma ∪ interactivityType ∪ interactivityLevel ∪ SemanticDensity ∪ LearningResourceType
13. LOforActive := (active ∪ mixed)) ∩ (exercise simulations experiment)
14. InteractivityType := active ∪ mixed ∪ expositive
15. InteractivityLevel := verylow ∪ low ∪ medium ∪ high ∪ veryhigh

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16. SemanticDensity := verylow $\cup$ low $\cup$ medium $\cup$ high $\cup$ veryhigh
17. LerningResourceType = exercise $\cup$ experiment $\cup$ definition $\cup$ algorithm $\cup$ example $\cup$ slide $\cup$ index

Example of Rules

Rule1: Activelearner(?x) $\wedge$ hasLearningStyle(?x,?y) $\wedge$ defineLOforActive(?y, ?z) $\rightarrow$ recommend(?x,?z)
Rule2: Reflectivelearner(?x) hasLearningStyle(?x,?y) $\wedge$ defineLOforReflective(?y, ?z) $\rightarrow$ recommend(?x,?z)

From the family ontology extracting above, the initial relations are identified to be member of the class. Finally adding rule mapping ontology knowledge to them, like Rule1 and Rule 2 etc.

IV. Leraning Object Recommendation model

In our work we design the multi agent- based learning object recommendation system and implement some of the important functions of each agent to show recommendation algorithm results.

A. Learner Interface Agent

The learner interface agent detects any user interaction with the learner interface and records the results, if any, of these interactions. When the learner first logs in, the learner interface agent reads the given username and password and passes this information to the learner model agent, which then accesses the learner's profile. When the learner completes a questionnaire, or other fill out feedback, the interface agent passes the responses and results to the leaner model agent. This information is used to build a model of the learner's abilities and how they view their own experience to date.

B. Learner Model Agent

The learner model agent is responsible for maintaining, updating and analyzing the learner profile. The learner model agent uses a learning object selection rule to create the learner preference set (LPS). Then, the negotiation between learner model agents and learning object recommendation agent will happen when the learner sends the recommendation request via learner interface agents.

C. Learning Object Recommendation Agent

The learning object recommendation agent needs learner's information from learner model agent to compute the preference score of each learning object. Moreover, it provides the ranking process and recommends the most compatible learning object to the learner via the learner interface agent.

D. Feedback Agent

For adaptation of the system, the feedback agent will be designed for learner feedback to the recommended learning objects. If the learner does not satisfy to them, the learning object selection rule or the learner model will be updated and the all process of recommendation will be restarted.

For demonstrating the result of learning object recommendation algorithms in this work, we implement some functions of recommendation and learner model agents. The class diagram in Fig.5 shows the detail of each class.

In conclusion, the multi agent-based learning object recommendation is strongly based on a continuous interaction among involved agents: such an activity is facilitated by the choice of XML for both representing agent ontologies and handling data exchange.

E. Preferred feature-based Recommendation Algorithm (PFB)

The values of the feature of a learning object can help determine if a learner may prefer the learning object. For example, under the future format of learning objects, learning object may compose of various media, such as text document, audio/video, picture, and etc. Different learners may prefer different formats of learning objects for the same concept depended on their learning styles. The preferred feature-based algorithm is to bias the learning objects with a learner's preferences. Learning object tending to suit a learner's preference more will get higher priorities when it is ranked to the learner. The weighted feature preferred feature-based (WF-PFB) was proposed for selecting the most suitable learning object to the learner. We present the detail of each variation in the following subsections.

F. Weighted feature preferred feature-based (WF-PFB) recommendation

In WF-PFB, the learning object feature is weighed by using the frequency that target feature is referred in learning object selection rule. We note that the frequency of learning object features when are referred in a learning object selection rules are different In WF-PFB, ù is computed by $\omega = \dfrac{1}{\sum F_i \text{ appearing in each Rule}}$ and the result of ù of learning object features are shown in the preferred feature-based algorithm.

ALGORITHM : Preferred Feature-based Algorithm

<u>INPUT</u>: Learner preference set *(LPS)*
Specific learning object set *(LOS)*
feature frequency weight (ù)
NWF-PFB , ù = 1 for each learning object feature i or
WF-PFB, ù = $\dfrac{1}{\#of\ RF_i}$, RF is the frequency of referring feature.
<u>OUTPUT</u> : Preference Score *(PS)* of specific *LO*
FUNCTION: Preference_Score_Calculation ()
FOR EACH *LPS*
FOR EACH *LOS of LOi*
INT *PS = 0*
//compute all of learner styles {A, R, S, I, B, U, Q, G} in LPS
FOR EACH PF_i *Î LPS (L)*

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IF $(PF_i = F_i)$ *and FWi<>0*
THEN $PS = PS + 5Ø—ß FW_i$
BREAK
RETURN *PS*
END FUNCTION

The information of the learner model in our experiment that presented is used to be an input for learning object recommendation.

We can generate the information about learners by using the definition 1 from Section III:

SLS_{001} = {(A,0), (R,1), (S,0.5), (I,0.5), (U,0), (B,1), (Q,0), (G,1)}

SLS_{011} = *{(A,1), (R,0), (S,1), (I,0.5), (U,1,), (B,0), (Q,0.5), (G,0.5)}*

SLS_{027} = {(A,1), (R,0), (S,1), (I,0), (U,1,) (B,0), (Q,1), (G,0), }

Then, by using the learning object selection rules such as, The LPS of leaner ID 001 can be defined by defining 3 as follows:

LPS_{L1} = {({exercise, simulations, experiment, active, mixed},1), ({simulation, experiment, 8, 9}, 0.5), {definition, exercise, 5, 6, 7}, 0.5), ({video, image, animation, simulation, 3, 4, 5},1), ({image, index},1)}

For example, the concept of "Process" of Operating System course is used to demonstrate learning object recommendation for the learner. The information about related learning object is represented as follows:

LOS_{001} ={ animation, active, 4, 8, simulation }
LOS_{002} ={ text , expositive, 2, 7, algorithm }
LOS_{003} ={ video , active, 4, 7, definition }

When using the Preference-contented based algorithm for computing the PS of each LO of Learner ID 001, the results are PS(LO_{001}) = 0.79, PS(LO_{002}) = 0.04 and PS(LO_{003}) = 0.45. Therefore, the recommended order is LO1, LO3 and LO2**.**

G. Evaluation Method

Each learner has to return preferred feedback (learning object ID that they most prefer) after he/she has studied every learning object in the same concept. To understand how the recommendation results affect learners, both of feedback analysis and *Preference error (PE)* between the real learner's preference and the system predictions will be compared.

Observing the learner's feedbacks directly is to understand whether the proposed model recommends learning object in accord with learners' preference, while calculating PE shows whether it can infer learner's preference and interest accurately or not. The prediction accuracy is better when the PE value is lower. In the experiment, different variety of algorithms will be demonstrated to show the different results. PE can calculate by using the following equation:

$$PE = 1 - \frac{\sum_{i=1}^{N} (LO_{ac} \cap LO_{pd})}{N}$$

where LO_{ac} is an actual referred learning object, LO_{pd} is the recommended learning object from the algorithm and *N* is the number of learners.

Among the various recommendation algorithms studied in this thesis, Weighted Feature-PFB is quite good accuracy in every group of learners (predict with an average PE of about 0.1977). Therefore, using Weighted-Feature-PFB algorithm has the highest PE for this evaluation learner data in our domain.

V. Conclusion

This paper has described an ontology-based modeling strategy that has been employed by an adaptive educational hypermedia, recommendation system and learning style-based adaptation. The ontology-based model constructed from the potential knowledge and competence state of the learner. We design the model based on multi agent-based, it is strongly based on a continuous interaction among involved agents: such an activity is facilitated by the choice of ontologies and handling data exchange. As the results in all of objectives, they give us to know what important process that learning object recommendation need. Being able to identify the learning style of the learner is an important step, since it can be used to raise learners' awareness regarding their strengths and weaknesses in learning as well as give instructors valuable information regarding the learning preferences they should try to accommodate in their course. In the context of research, learning style diagnosis is the prerequisite for adaptation provisioning. Then, the efficiency learning object recommendation was used to help us in providing the most compatible learning object to the learner.

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